Evaluating downscaling methods for seasonal climate forecasts over East Africa

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SERVIR and Seasonal Climate Forecasts

- The NASA/USAID SERVIR project is dedicated to developing and improving the capacity of several hub regions to incorporate unique NASA satellite and modeling resources into operational environmental monitoring and planning. Recent and currently served hub regions include Mesoamerica, East Africa (EA), and the Hindu Kush-Himalayan region.
- The SERVIR Applied Science Team (AST) has recently been established with the goal of providing enhanced products for use in the hub regions. Currently awarded projects within the AST include (but not limited to) agricultural and hydrologic impact modeling, air quality and landslide assessments.
- Another AST team is focused on the evaluation of climate model simulations and the development of downscaled scenarios to be used by AST projects focused on impact modeling. Results presented here focus on the initial development of downscaled seasonal forecasts from the NASA Global Modeling and Assimilation Office (GMAO) GEOS-5 model contribution to the U.S. National Multi-Model Ensemble (NMME) for use in agriculture and hydrologic modeling over East Africa.

Observed East Africa Rainfall Variability

Seasonal rainfall in East Africa (Fig. 1) is strongly tied to the annual march of the Intertropical Convergence Zone (ITCZ). The result is an annual maximum in rainfall in northern (southern) East Africa during JJA (DJF) and biannual maxima near equatorial East Africa (5S-5N) in MAM ("long rains") and OND ("short rains"). The topographic influences on seasonal rainfall are pronounced with the largest seasonal rainfall occurring over the interior highlands (see Fig. 3 for elevation). Interannual variability of seasonal rainfall is locked strongly to the seasonal cycle.

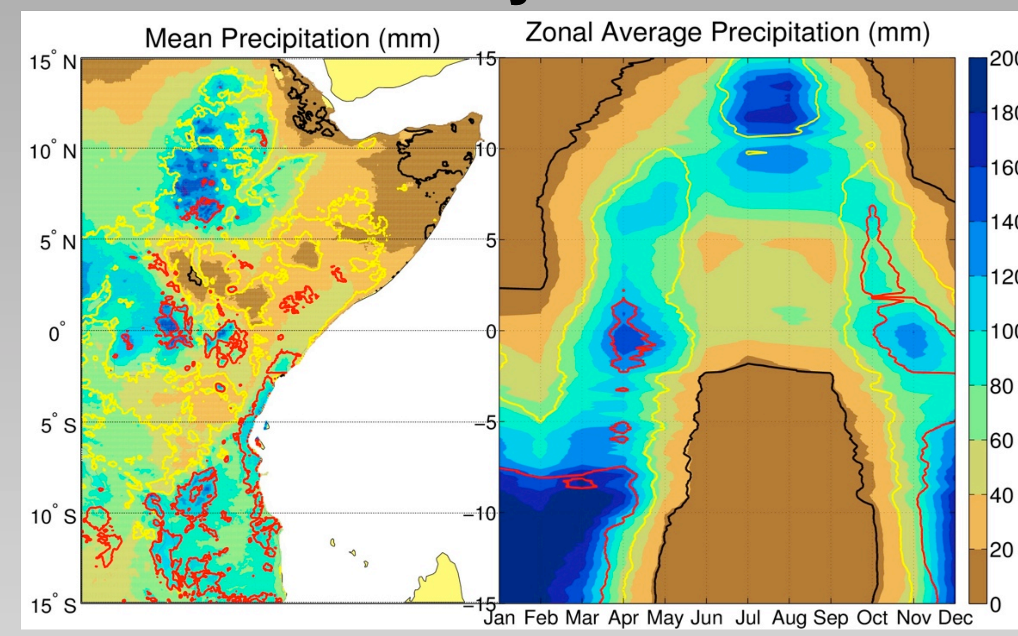

Figure 1. (Left) Average monthly rainfall (mm) is shown together with the magnitude of interannual variability (contours, black=10mm, yellow=30mm,red=50mm). (Right) The meridional march of seasonal rainfall and timing of strongest interannual variability is illustrated. Note EEA bi-annual rainfall maxima.

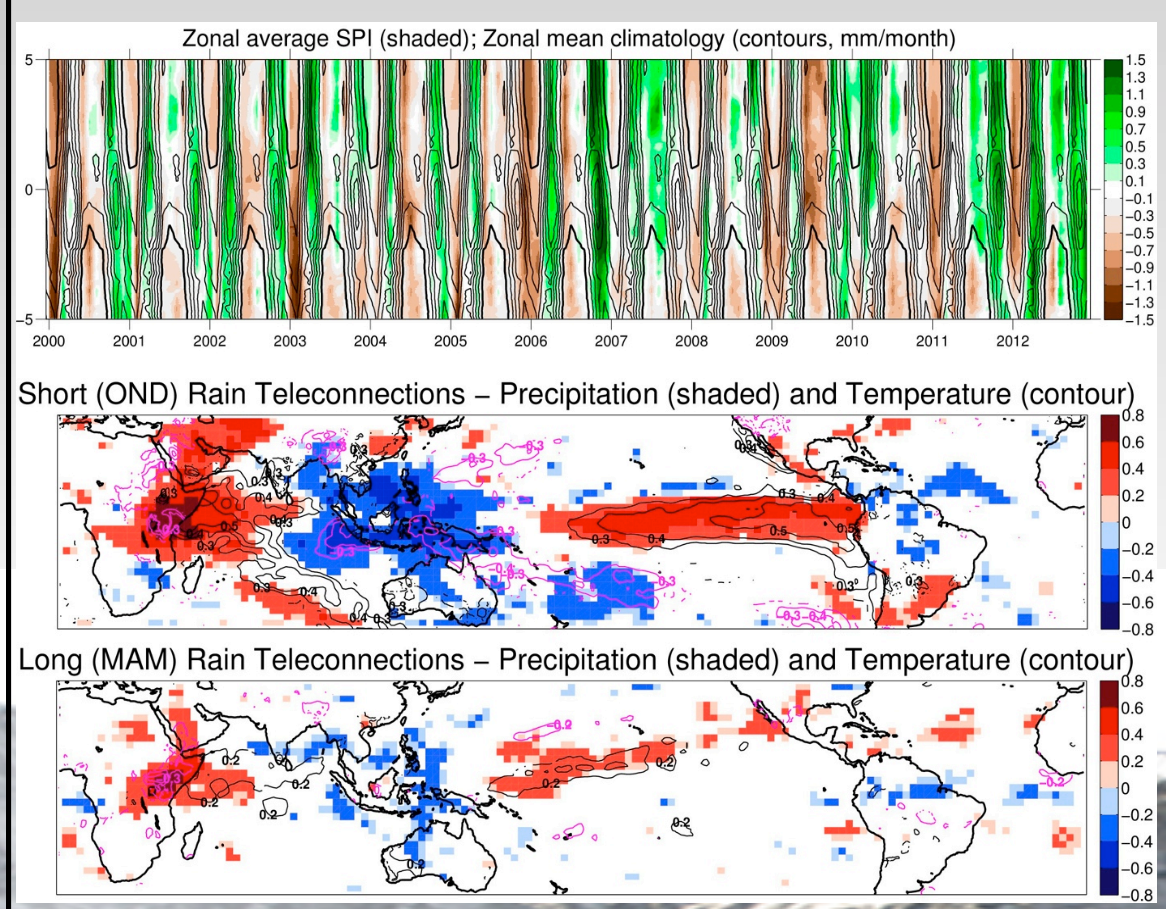

Figure 2. (Top) Zonal average (30E-45E) SPI is shown for EEA (5S-5N). |SPI| values less than about 0.5 correspond to the near-normal tercile. EEA area-averaged rainfall SPI is correlated to observed precipitation (shaded) and surface temperatures (contour) for the short (middle) and long (bottom) rainy seasons.

Equatorial East Africa (EEA) rainfall variability can be examined through use of a standardized precipitation index (SPI) that quantifies the anomalous variability (annual cycle removed) in relation to standard deviates of a normal distribution. Since 2000, EEA rainfall has shown significant interannual variability (Fig. 2) including excessive rainfall in late 2006 and the back-to-back failure of the short and long rains in 2010-2011.

Teleconnection maps for the short and long rainy seasons (Fig. 2) indicate significant relationships with both sea surface temperature (SST) and precipitation variability. These have been identified in several studies with short rain interannual variability linked strongly to ENSO-induced alterations of tropical zonal circulation.

Forecasting to Impact Modeling Framework

GCM Seasonal Forecast – Raw Model Output
- Coarse spatial resolution (~100 km)
- Typically archived at monthly resolution
- Systematic biases as a function of lead

Bridging the gap – "Downscaling"
Statistical downscaling makes use of large-scale model predictors together with observations to generate plausible high-resolution scenarios for assessing local-scale variability and/or driving end-user models. Spatial downscaling techniques vary widely including both linear and nonlinear (e.g. neural networks) methods. Techniques for generating sub-monthly variability include stochastic weather generators (univariate and multivariate) and analogue/resampling approaches.

Impact Modeling (e.g. Agriculture, Hydrology)
- Fine spatial resolution needed (~5 km)
- Need daily (or better) temporal resolution
- Realistic spatial and temporal variability needed

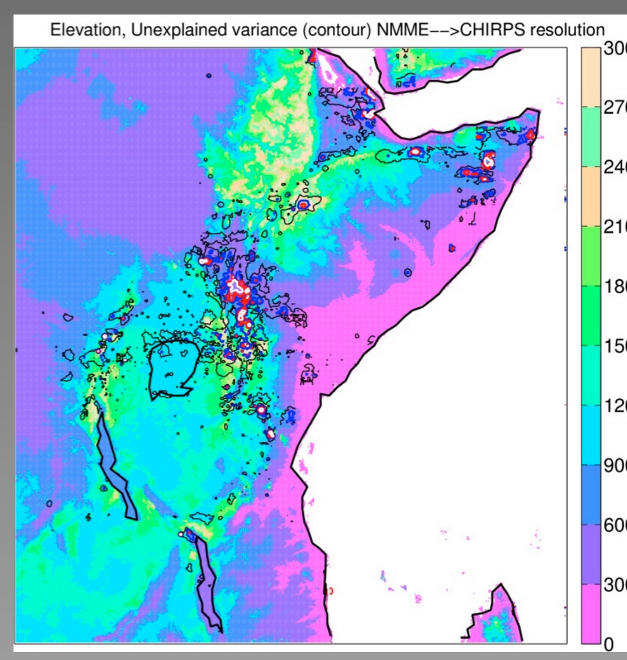

Figure 3. East Africa topography is complex including low-lying coastal areas and elevated interior highlands mixed with the Great Rift Valley. This leads to significant local-scale variability in rainfall. Using coarsely-resampled precipitation as a linear predictor of the fine-scale precipitation from which it was developed results in an inevitable loss of information. Some areas have residual unexplained variance of 10% (black), 20% (blue) 30% (red), and even 40% (white) arising from the scale mismatch.

Raw Model Skill and Bias Correction

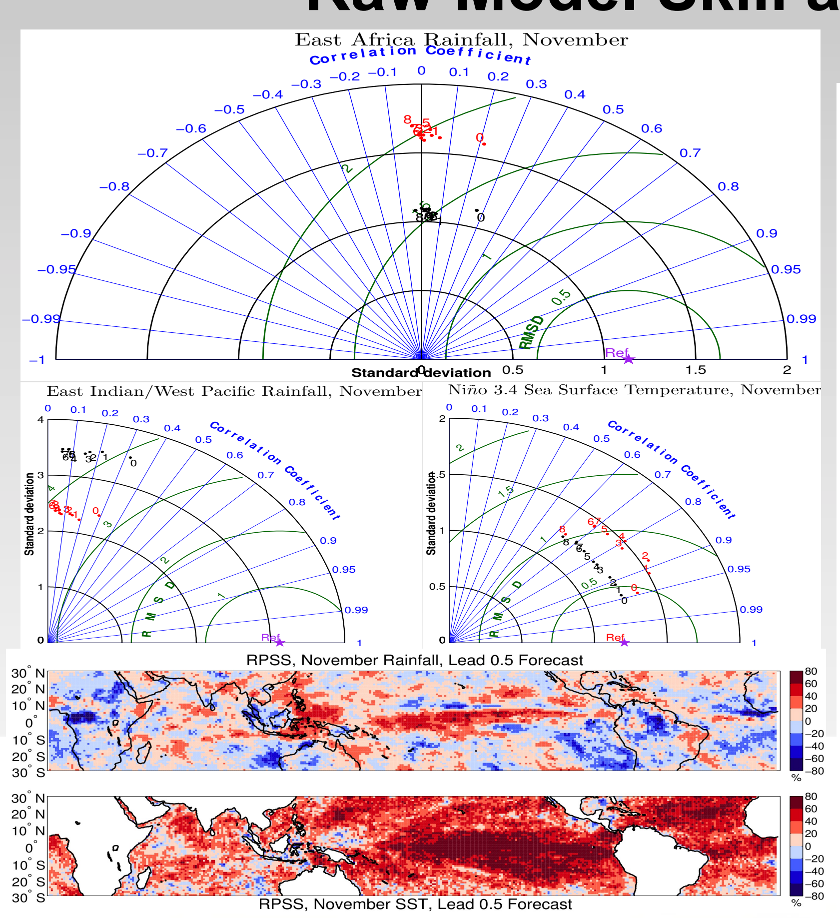

Figure 4. Taylor diagrams illustrate deterministic skill measures (anomaly pattern correlation, centered root-mean-square, and pattern standard deviation) for verification of East African November rainfall (top), West Pacific rainfall (middle-left), and Niño 3.4 SST (middle-right) from the NASA GMAO raw (red) and bias-corrected (black) seasonal forecasts for leads from 0.5-8.5 months. Note the significant reduction in skill with lead particularly for East African rainfall. RPSS for rainfall and SST (bottom) illustrates probabilistic skill improvements (positive) compared to climatological tercile probabilities.

Raw model simulated fields often contain systematic biases that vary as a function of lead. These can be corrected through methods such as quantile-quantile mapping that preserve rank correlation but provide improved amplitudes and spatial variability with respect to uncorrected model output (Fig. 4). There can be large differences in the inherent skill of models as a function of variable, location and forecast lead time.

Precipitation over East Africa exhibits low skill at all but the shortest lead, while Niño 3.4 regional sea surface temperatures show very high anomaly correlation out to many months. The ranked probability skill score (RPSS) at 0.5 month lead shows much improved skill prediction of ocean surface temperatures in many regions compared to climatological tercile probabilities. Precipitation forecasts show only limited skill and is primarily limited to the central and western Pacific Ocean.

Downscaling Results

Rather than using the forecasted precipitation over the East Africa region directly, the NMME set of hindcasts can be used to develop improved predictions of EA rainfall variability in the form of the EA SPI. Effectively, model output statistics are used to bridge model forecasts of large-scale variability to those of interest to this study.

Matched filter regression (MFR) is a technique that can be used to identify predictors of large scale variability that are significantly correlated with a predictand of interest. Hindcast simulations are used to identify significant correlations between the EA SPI and model fields (Fig. 5). Hindcasts of those regions exhibiting significant correlations are used to develop a multivariate vector whose entries are scaled by the correlation strength at each location. The set of hindcast vectors are subjected to a principal component (PC) analysis. The 1[st] PC serves as a predictor for deriving a functional relationship with EA SPI. The MFR approach shows significant improvement over the direct model forecasts of EA rainfall (Fig 6.).

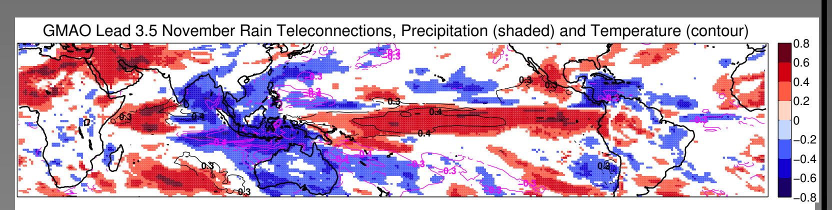

Figure 5. The GMAO seasonal forecast cross-validated correlations with East Africa SPI at Lead 3.5 are shown for precipitation (shading) and for SST (contour). These patterns can be compared to those from direct observations shown in Figure 1. Within several months of November, the NASA GMAO model demonstrates skill in capturing the large-scale precipitation and sea surface temperature patterns associated with interannual SPI variability.

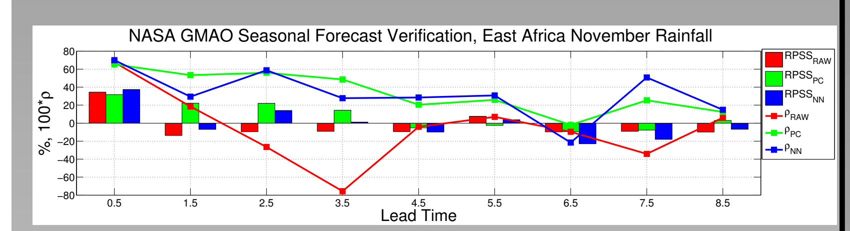

Figure 6. The GMAO seasonal forecast cross-validated verification of SPI predictions from the MFR are shown. The RPSS (bars) and correlation (line) measures are shown as a function of lead time for downscaling to the SPI using the bias-corrected forecasted East Africa average precipitation (RAW), the MFR approach using bivariate regression of the 1[st] principal component (PC), and a neural network regression of the 1[st] PC (NN). Note how rapidly the skill drops using only the forecasted precipitation over East Africa. In contrast, the MFR based approach maintains skill for several months, with PC outperforming the NN approach.

Summary Points

- The NASA/USAID SERVIR Applied Science Team (AST) is currently supporting several projects that will make use of downscaled seasonal forecast scenarios in agricultural and hydrologic modeling outlooks for East Africa.
- Interannual rainfall variability in equatorial East Africa is prominent, leading to floods and droughts. Variations in both the short and long rains are influenced by ocean-atmosphere teleconnections.
- Seasonal forecasts from the GMAO model show limited inherent skill for direct forecasts of EA rainfall and must be spatially and temporally downscaled for use in impact modeling.
- Matched filter regression, combined with bootstrap resampling of a high-resolution historical record, may be a useful approach to the development of refined scenarios for use within the SERVIR AST.